Lanzarote, 20th April 2018

CT4: Climate prediction in the Tropical Atlantic

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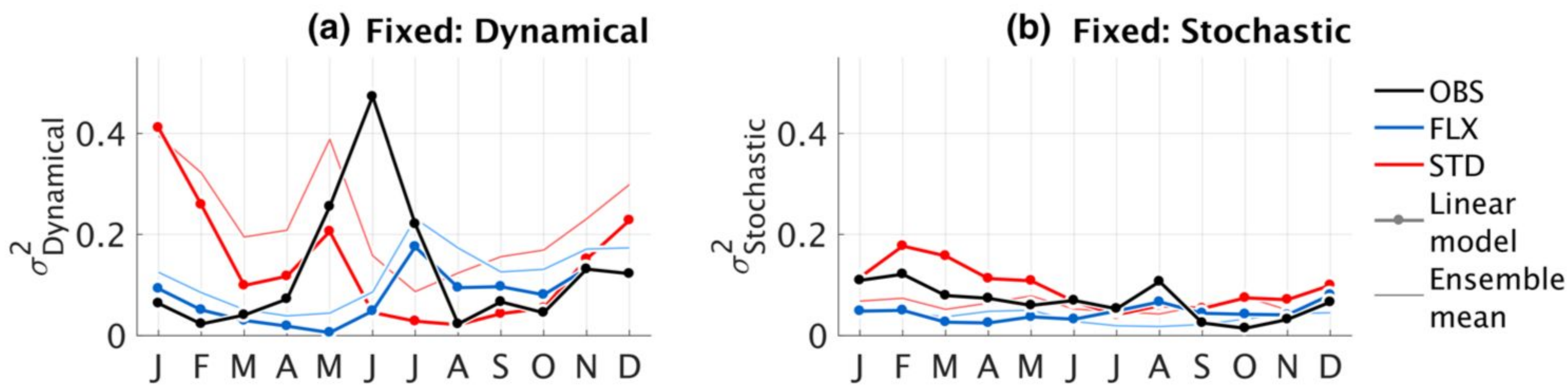
CT4: Climate prediction in the Tropical Atlantic

CT4 will increase understanding of climate predictability in the region and evaluate the impact of model systematic error on climate prediction, through experiments incorporating model improvements (from CT2&3) and bias correction techniques

- **WP9** improve our understanding of Tropical Atlantic variability on seasonal and longer time scales and its global impacts
- **WP10** Statistical methods to assess and improve forecast of Tropical Atlantic variability
- **WP11** Impact of model improvement and systematic error reduction on climate prediction and projection

Improving our understanding of Tropical Atlantic variability

Variance in summer SST in the eastern Equatorial Atlantic is **dynamically** controlled (Dippe et al. 2017). However, most current state-of-the-art atmosphere-ocean coupled models are not able to reproduce properly such result [Dippe et al. 2017; Nnamchi et al. 2015].



Partition of ATL3 variance into dynamical (left) and thermodynamical (right) components for observations (black) and model simulations in a standard configuration (red) and in a flux corrected one (blue) [from Dippe et al. 2017]

The processes acting in the development of the Atlantic El Niño can be different in observation and in models [Polo et al. 2015].

Improving our understanding of Tropical Atlantic variability

What is the impact on variability and predictability of the wind stress in the Equatorial Atlantic?

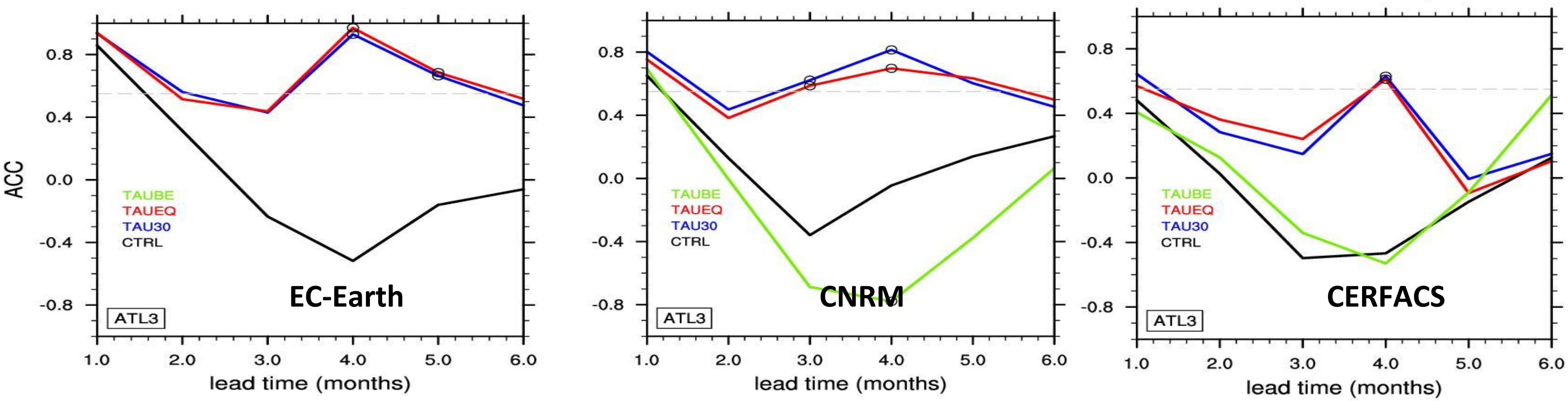
Performed sensitivity simulations where windstress is replaced over the Equatorial Atlantic (3S-3N) by ERAinterim - Seasonal Predictions

Improving our understanding of Tropical Atlantic variability

Correcting the wind stress in the Tropical Atlantic results in

- higher skill in predicting Tropical Atlantic SST
- an improvement in the representation of the teleconnection between the the summer Tropical Atlantic and the winter Tropical Pacific SST [Rodriguez-Fonseca et al., 2009]
- higher skill in predicting the winter Tropical Pacific SST

Skill in ATL3



Experiments performed in coordinated sensitivity study in WP6 [Voldoire at al, in prep, 2018] and skill analyzed by Sanchez Gomez E. [D11.1 deliverale]

Improving our understanding of Tropical Atlantic variability

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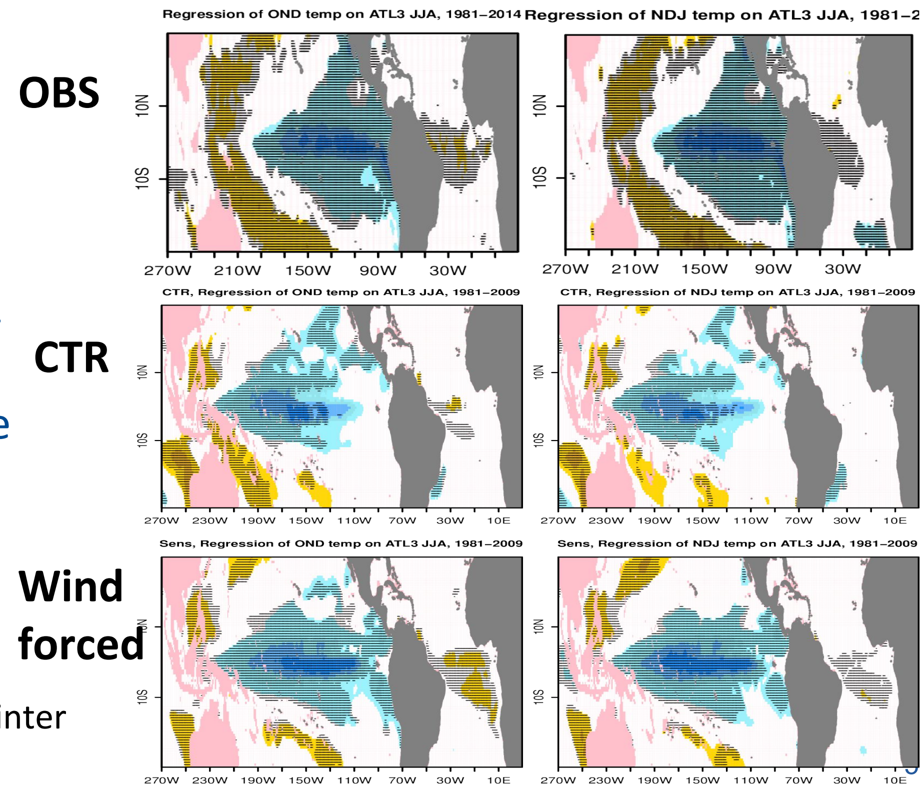

Results from EC-Earthv3.1

Exarchou E., Rodríguez de Fonseca et al., in prep

Lagged regression of summer ATL3 on winter SST (OND left and NDJ right)

Improving our understanding of Tropical Atlantic variability

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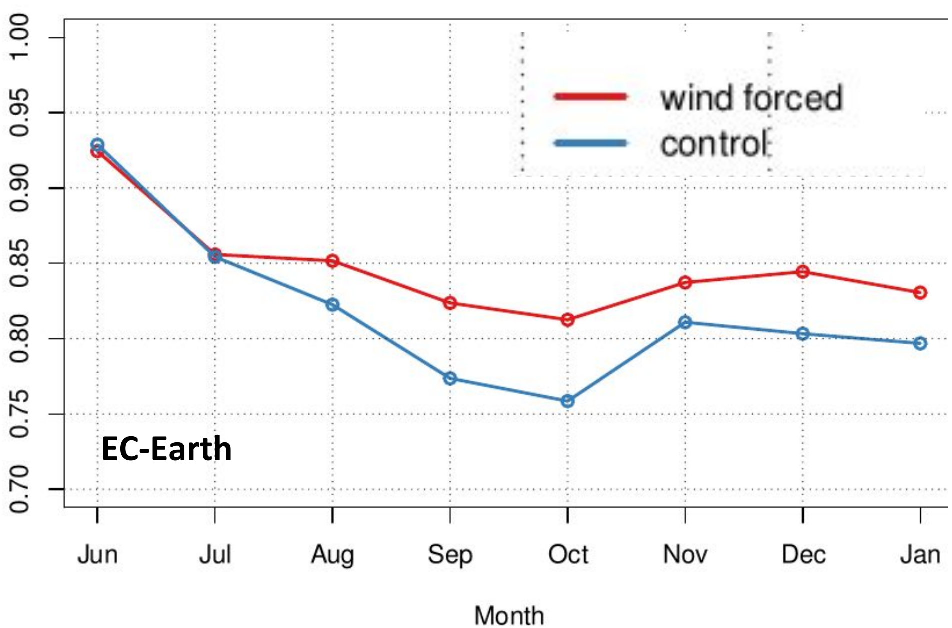
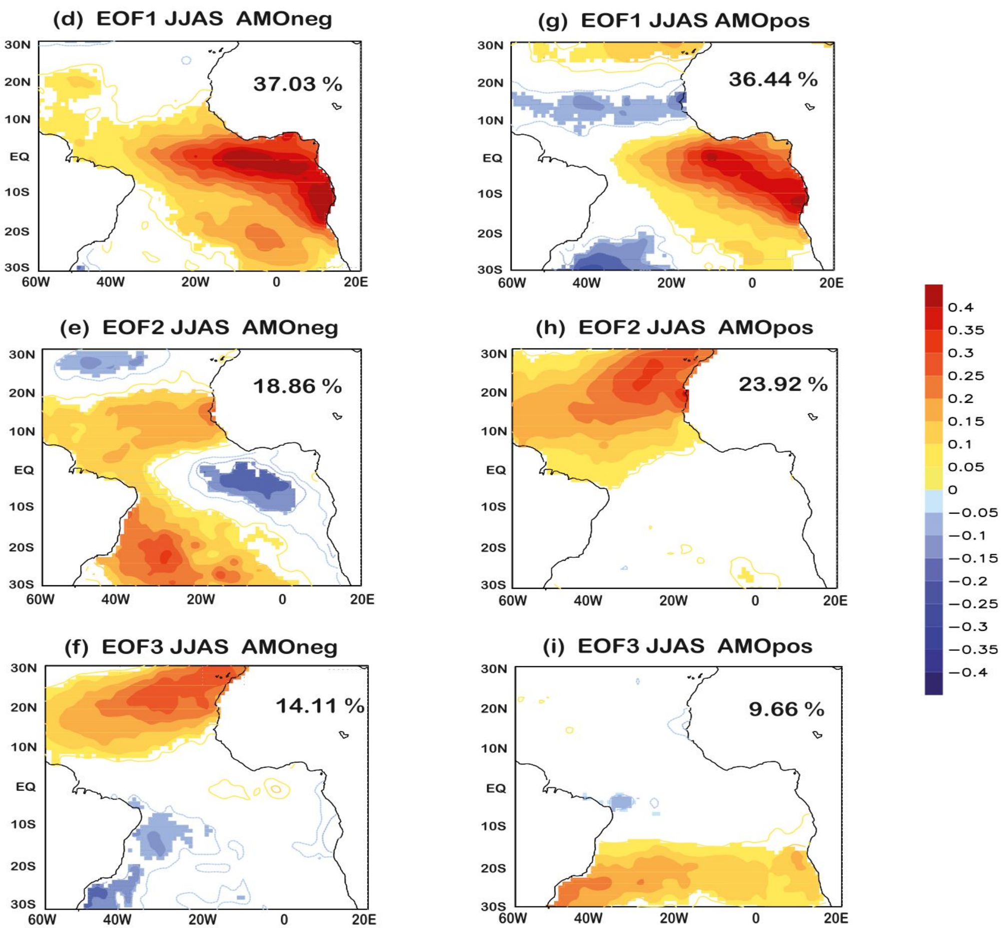
Skill in Niño3



Exarchou E., Rodríguez de Fonseca et al., in prep

Improving our understanding of Tropical Atlantic variability

The characteristics of the Atlantic El Niño change depending on the background state (Martín-Rey et al. 2018).

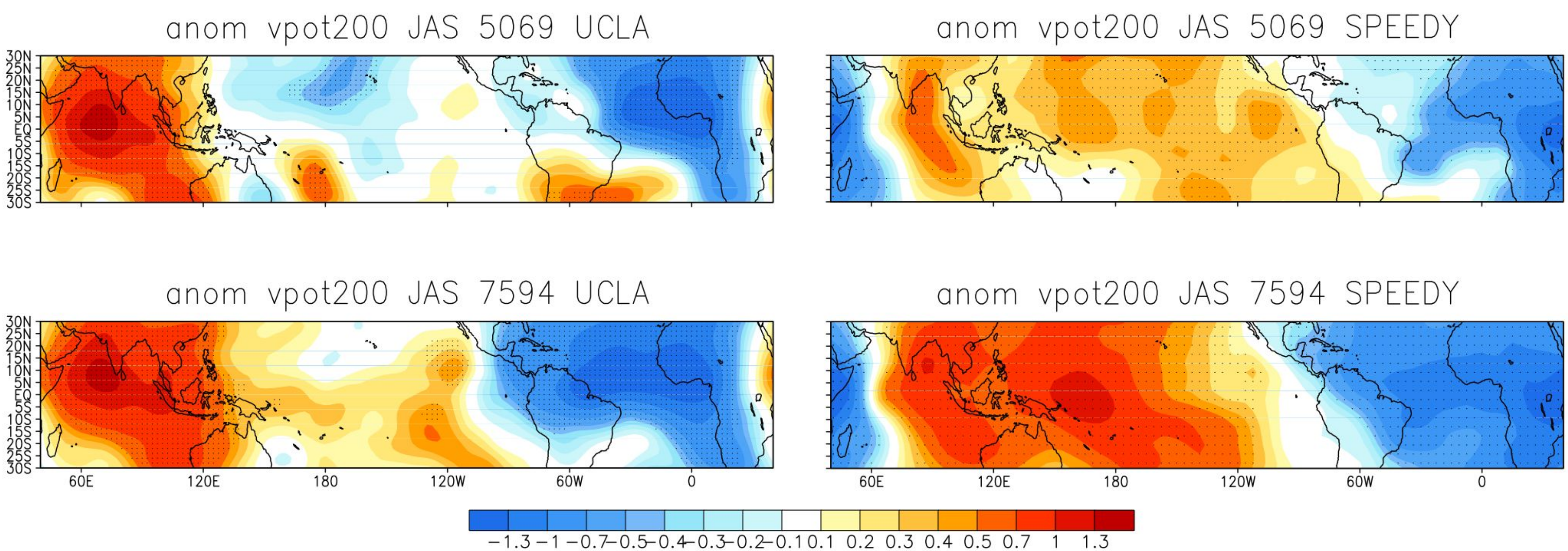


First three EOFs of interannual tropical Atlantic [308N–308S, 608W–208E] variability in June–September (JJAS) AMO negative (left) and AMO positive (right) phases [Martín-Rey et al. 2018].

In AMO negative phases the Atlantic El Nino appears as combined mode with the Pacific El Nino leading interbasin variability

Improving our understanding of Tropical Atlantic variability

The changes in the characteristics of the Atlantic El Niño lead to changes in the impact on the Pacific atmosphere in the next winter: changes in the Walker Atlantic–Pacific cell produced by the Atlantic El Niño are stronger after the 1970s (negative AMO phase), and are reinforced by the change in the impact of the Atlantic El Niño over the Indian Ocean and the Maritime Continent [Losada and Rodriguez-Fonseca 2016].



Impact of the Atlantic El Niño pattern before the 1970s (top) and after the 1970s (bottom) simulated by two AGCMs in velocity potential at 200 hPa (106m2s-2) [Losada and Rodriguez-Fonseca 2016]

Statistical methods to assess climate model biases

WP10 developed a general statistical methodology for the quantitative spatial, temporal and spatio-temporal assessment of systematic climate model errors

THE UNIFIED FRAMEWORK IS:

BAYESIAN (we can incorporate information from different sources, including expert knowledge)

HIERARCHICAL (we treat errors at data, process and parameter level separately and in a transparent way)

KEY ASPECTS OF THE METHODOLOGY:

D(s,t) = M(s,t) – O(s,t) D=empirical model error, M=model output, O=observation in space and time

D is what is usually investigated… instead we posit that the true model error is a (directly) unobservable process (STATE-SPACE APPROACH):

D(s,t) = FD(s,t) + e(s,t) D= true model error (process), e= Gaussian noise, F=observation operator

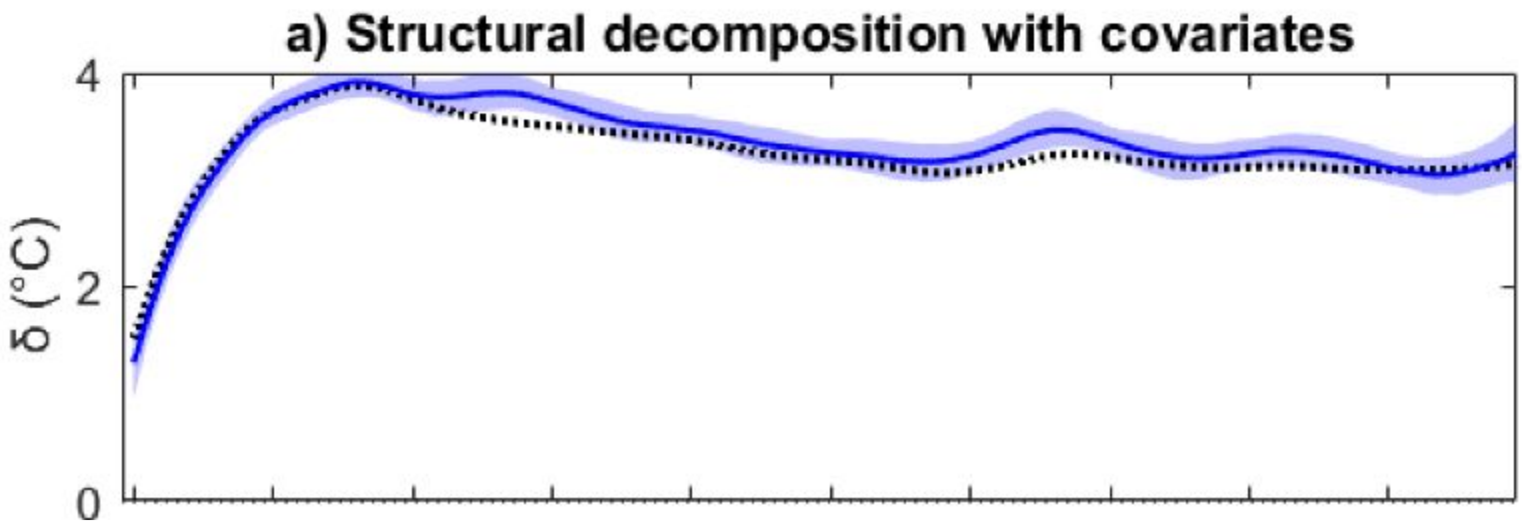
D(s,t) = GD(s,t-1) + m(s,t) G=process operator, m= Gaussian noise

Definition of the process equation is flexible, so good for different applications. We can distinguish/model different spatial (large-scale vs small-scale) and temporal (trends, seasonalities, forced responses) components. Note that we model the noise at the process level: better quantification of uncertainty!

Statistical methods to assess climate model biases

An example of flexibility: the purely temporal approach can be used to test hypotheses about the generation and propagation of systematic decadal climate prediction errors (drifts)

Case study: MiKlip prototype system for decadal climate predictions, SST errors in the Angola-Benguela front region

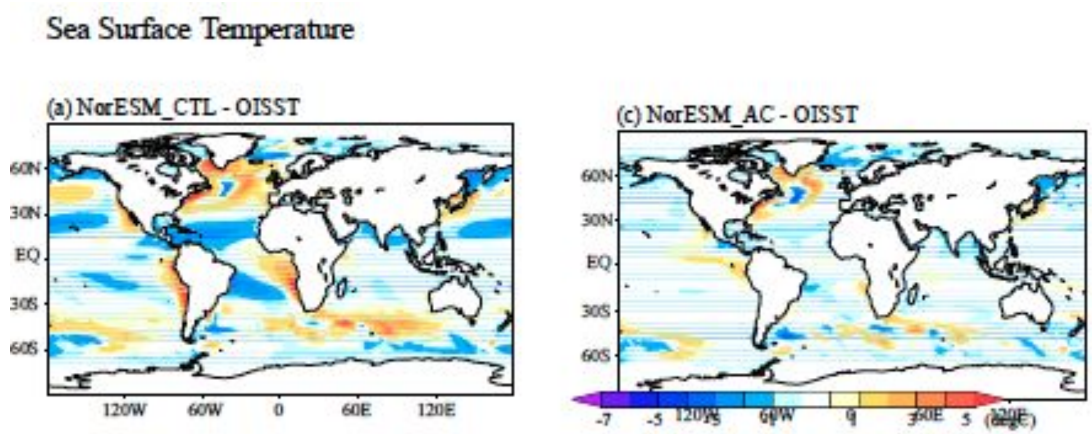


MIXED LAYER HEAT CONTENT ERROR: drift estimation does not change appreciably, implying little explanatory effect

[Zanchettin et al. 2017, SciRep; Arisido et al., 2016 SERRA; Arisiso et al., 2017, under review]

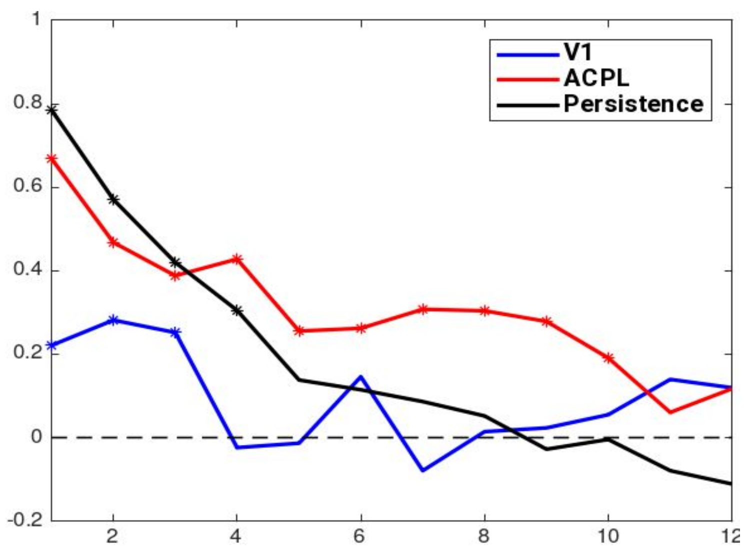
Impact of model systematic error reduction on climate prediction

Climate Prediction with bias-corrected CGCM (NorESM): Anomaly Coupling



Substantial reduction of tropical and subtropical biases by anomaly coupling [Toniazzo and Koseki, under review, JAMES]

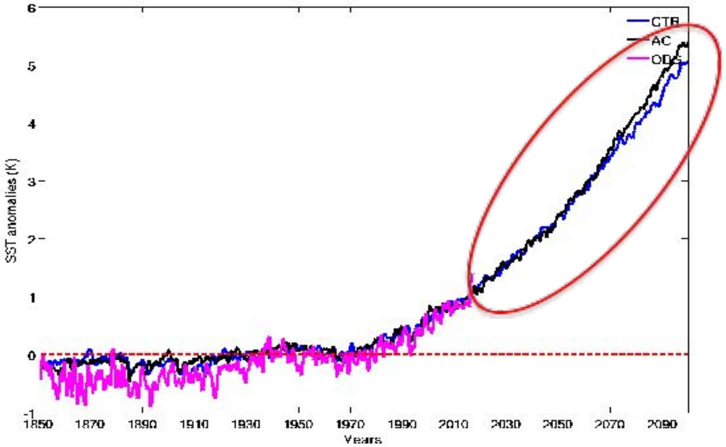
Reducing mean biases enhances seasonal prediction skill for the Atlantic Niño



Prediction skill of Atl3 1980-2014, 4 starts per year (Feb. May, Aug. Nov.), 9 ensemble members for NorCPM [Lea Svendsen]

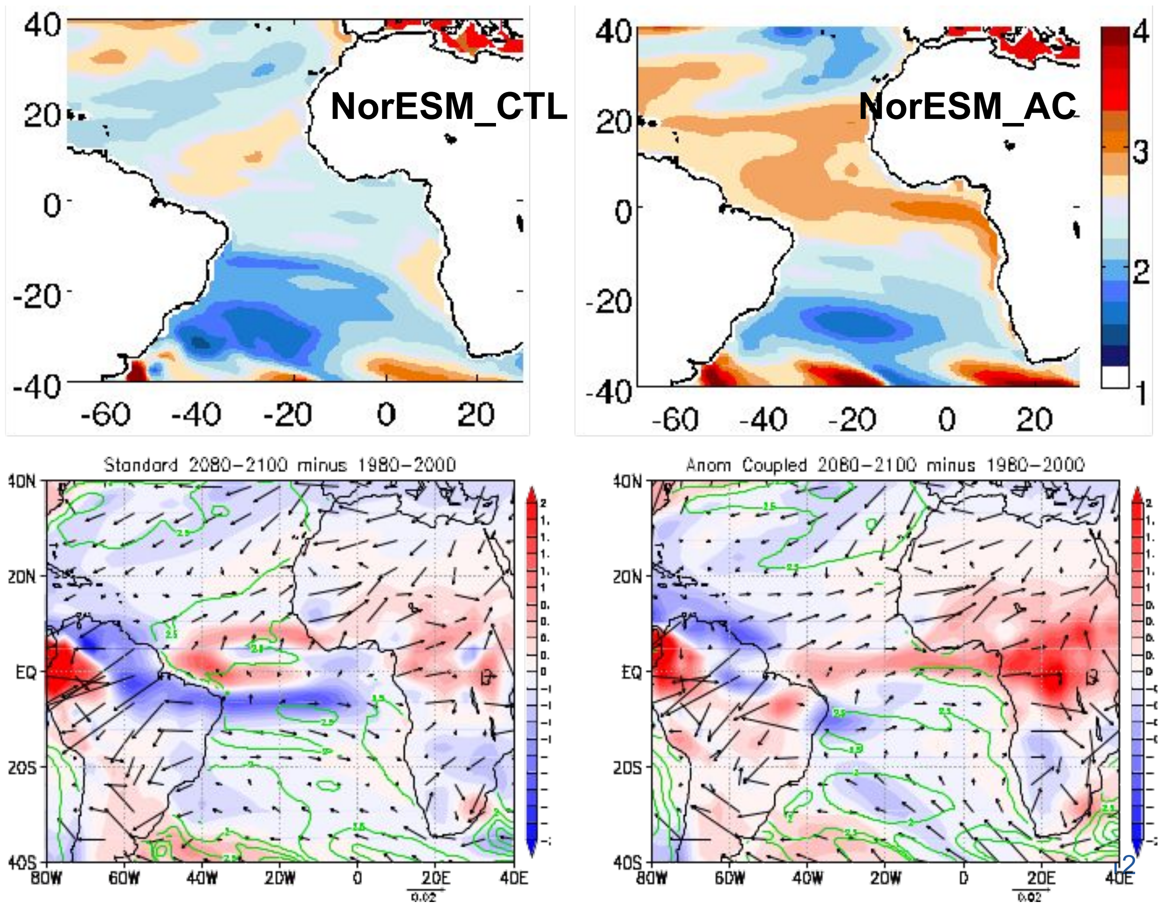
Courtesy: Francois Counillon

Impact of model systematic error reduction on climate projection



Higher sensitivity of SST to the global warming in projection with anomaly coupling
[Koseki S. , Teferi D]

Response to the global warming: 2080-2099 and 1980-2000 difference

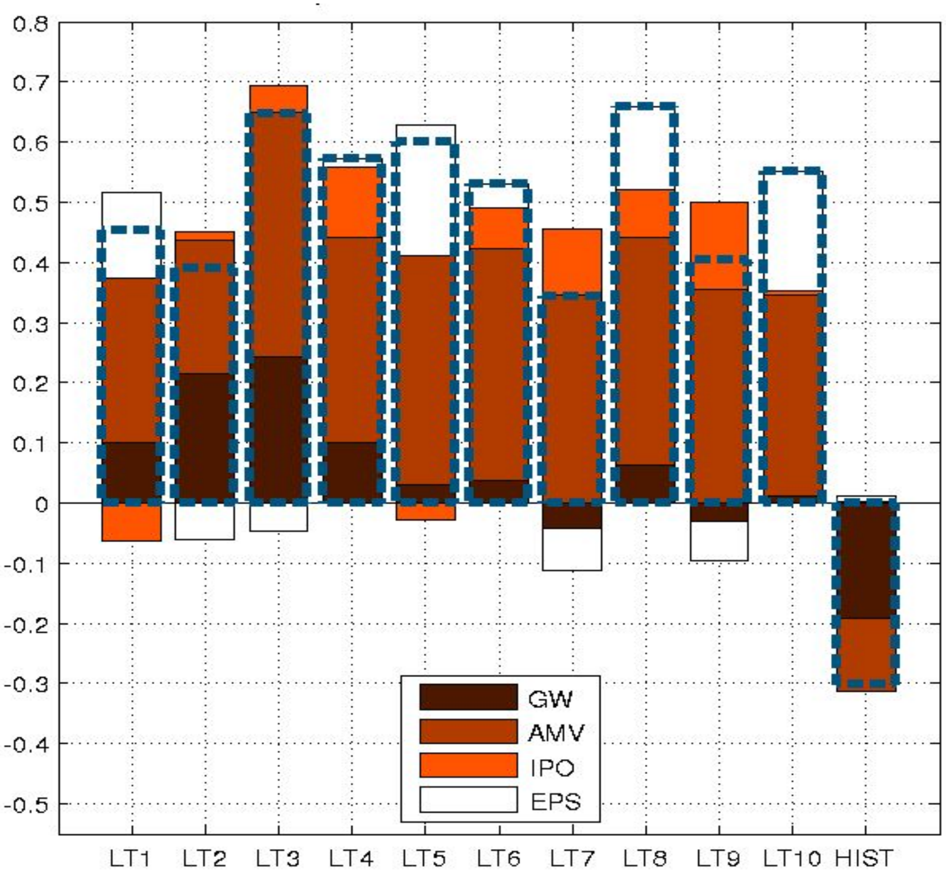


- Weakening of the cold tongue is stronger in bias corrected version

- Correspondingly, westerly and wet anomalies are more enhanced at the equatorial Atlantic

  [Koseki S. , Teferi D]

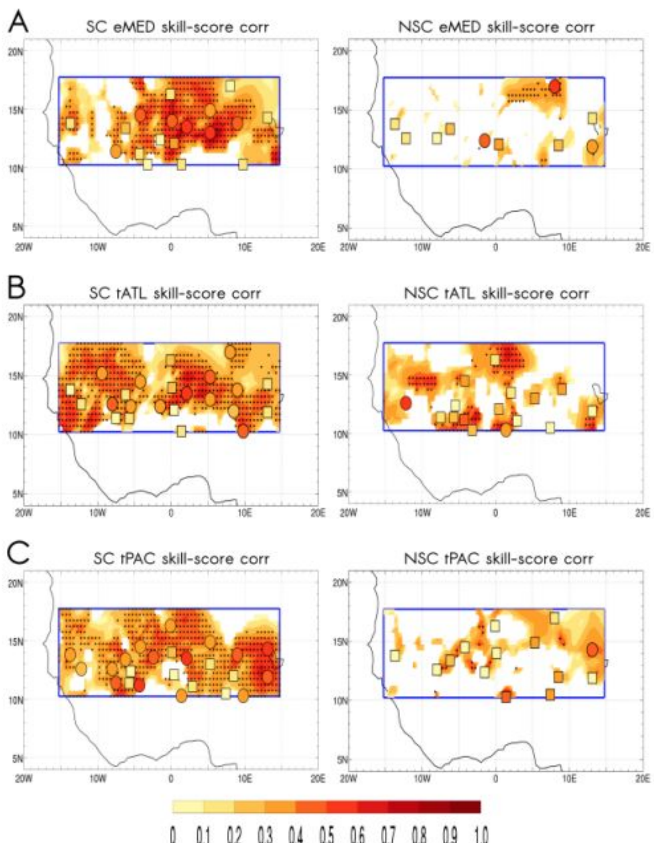
Sources of prediction skill in Sahel rainfall



The ACC skill scores for each of the 10 lead times in the decadal hindcast and the historical experiment (blue dashed bars) and its decomposition into four terms following the multi-linear regression analysis, which are due to: GW, AMV, IPO and the residual of the fit (labeled as EPS).

The main source of skill in the decadal hindcast of West African rainfall is from the AMV. The GW signal degrades skill at some lead times [Mohino, et al. 2016]

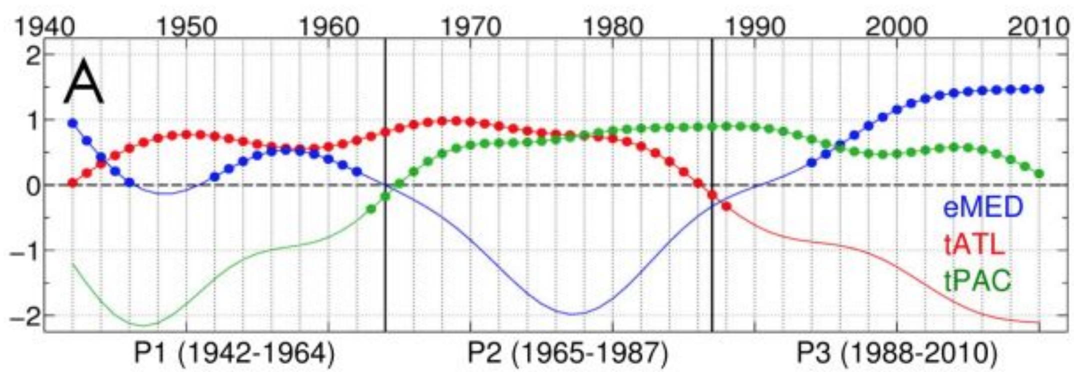
Source of predictability Sahel: interannual



The crossvalidated skill score for interanual rainfall is enhanced over the Sahel in some decades with respects to others for Mediterranean, tropical Atlantic and tropical Pacific SST predictors .

There is a clear modulated SST-influence at multidecadal time scales.

From Suárez et al (2018, J. Climate, in press)

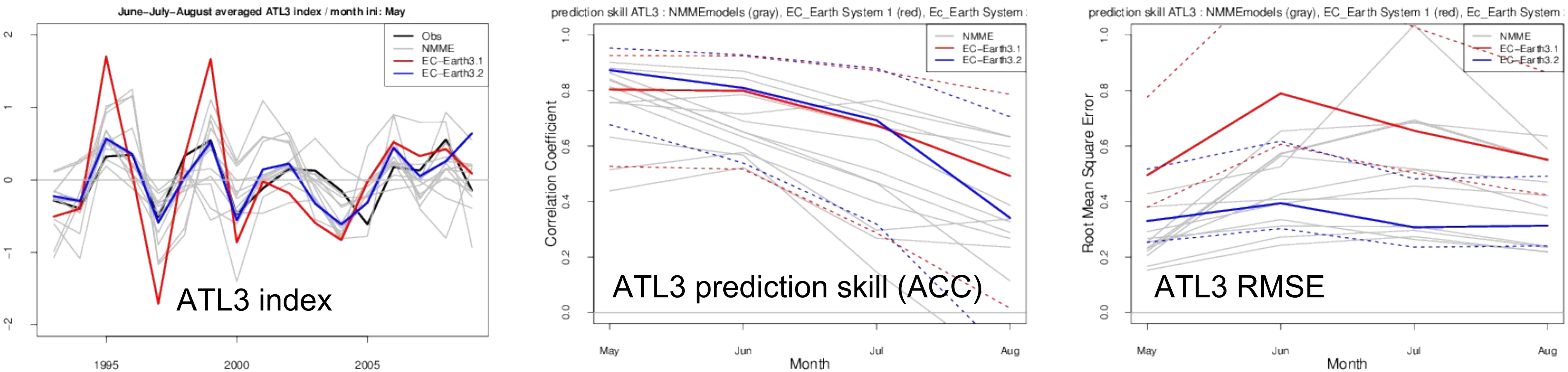


SC periods are dotted

NSC periods are not dotted

Assessment of the prediction skill in new seasonal forecast systems

The performance of the new EC-Earth forecast system is clearly improved in representing the magnitude of the variability, even if there is no clear improvement in terms of the anomaly correlation coefficient.

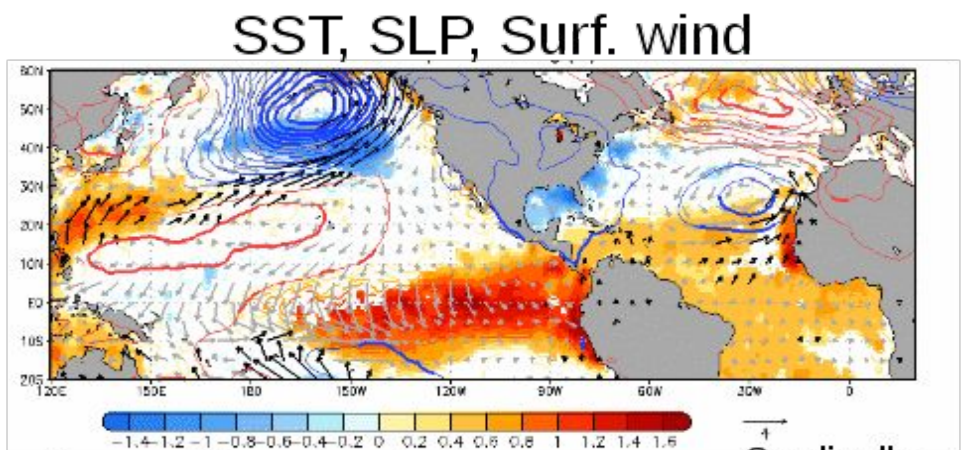


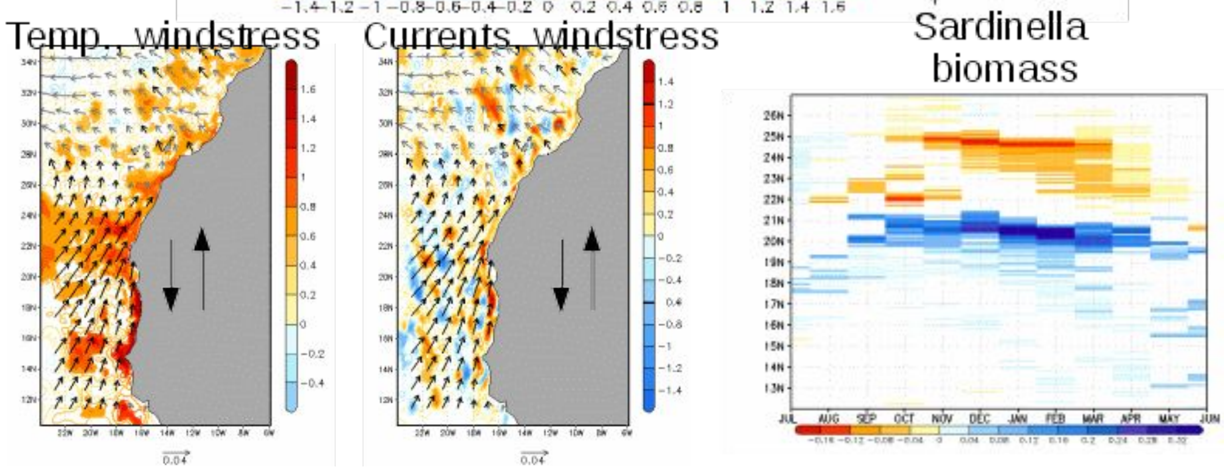
June-July-August ATL3 index from observation (black line; dataset: erasstv4), NMME forecasts (gray lines), EC-Eartv3.1 system (red line), and EC-Earthv3.2 system (blue line). ATL3 ACC (middle) and RMSE (right) score. The dashed line on the ACC and RMSE plots indicate the 90% confidence interval of EC-Earth systems.

Cooperation between CT4 (ocean/climate) and CT5 (fisheries)

Cooperation between CT4 (UCM and UNIVE, **López-Parages**, Rodríguez-Fonseca, N. Keenlyside) and CT5 (T. Brochier and P. A. Auger from WP12)

El Niño influences the migrations of round sardinella off northwest Africa
(given its recent finding the study of related statistical properties/methods represents an ongoing work)





López-Parages et al (in prep)

Challenges, opportunities, lessons etc

- **Challenges**

Computational costs of BHMs: how to move from a regional to a global framework?

- **Opportunities**

From bias estimation to bias correction, multivariate approach to bias/drift estimation, cascade of biases in nested models (e.g., downscaling or ecological impacts, see Jorge's work)

Improve the predictability of fisheries from SST teleconnections. From remote forcing to local effects.

- **Lessons for the future?**

Improve the dynamical representation of the Atlantic Niño in coupled models

Better representation of the ITCZ and its multidecadal variability to further understand non-stationarities in Atlantic Niño and SST-forced teleconnections with Sahelian rainfall